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Assessing direct and indirect emissions of greenhouse gases in road transportation, taking into account the role of uncertainty in the emissions inventory

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ABSTRACT

Greenhouse gas (GHG) concentration in the atmosphere has increased since the beginning of the industrial era, with dramatic effects on climate change. Transportation is one of the main sources of GHGs, with more than two-thirds of transport-related GHG emissions attributable to road vehicles. Any policy that aims to reduce GHG emissions needs robust measuring methods that guarantee the quality and reliability of primary data and estimates. However, these estimates are subject to uncertainty, both at the stage of compiling accounting tables and at the stage of using this information to formulate a specific policy question.

This paper considers how to reduce uncertainty in estimating GHG emissions from road transportation, with specific reference to a regional emissions inventory in Italy. We propose the application of a use-chain model that can tackle uncertainty in measuring GHG emissions by enhancing the quality of the emissions data registry in the inventory. This new metric, which we call emission value at risk (VaR), draws from methodologies and concepts employed in the insurance and financial sectors. Moreover, additional assessments are performed, integrating the inventory data with those available in the regional energy balance and disaggregated sectoral economic dataset. The results show that a sound accounting method enables uncertainty in emission data to be taken into account, thus improving the design of appropriate strategies to reduce GHG emissions.

1. Introduction

The increase in greenhouse gas (GHG) concentrations is attributed to the burning of fossil fuels and the intense urbanization process worldwide (IPCC, 2014). The consequence of this increase is global alteration of the climate, which causes adverse phenomena such as floods and droughts, modifications in the level and the patterns of precipitation, and heatwaves in cities.

On 12th December 2015, negotiations among the Conference of Parties (CoP21) concluded with the adoption of the Paris Agreement, a global climate deal to reduce carbon emissions and slow global warming. Article 2 of the Paris Agreement (UNFCCC, 2015) aims to "*[hold] the increase in the global average temperature to well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change […].*"

Paragraph 13 of article 4 states that "*[…] in accounting for anthropogenic emissions and removals corresponding to their nationally determined contributions, Parties shall promote environmental integrity, transparency, accuracy, completeness, comparability and consistency, and ensure the avoidance of double counting […].*"

Accurate estimates of GHG emissions are undoubtedly vital, both to measure and record emissions over time consistently and to provide reliable input to policy making processes and tools, especially with regard to adaptation to climate change.

The consistency and reliability of estimates can only be attained when uncertainty is minimized— inarguably, it is not possible to fully eliminate uncertainty, as any measurement contains some element of doubt inherent in the data/estimate. Researchers should, therefore, report not only the outcome of measurement but also the width of the possible error (i.e., the interval) and the level of certainty (i.e., the confidence interval) associated with the estimated value. According to the Intergovernmental Panel on Climate Change (IPCC) guidelines (IPCC, 2006), compiling a GHG inventory is a two-step process: (i) data collection, which involves the evaluation of existing sources of data and the planning of new emission measurements and surveys; (ii)

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uncertainty assessment, which must be applied to all relevant source and sink categories, GHG gases, and inventory totals. The second step is indeed crucial, not only in inventory compilation but also in the use of data drawn from the inventory.

Transportation is a hugely important source of GHGs within the European Union (EU), responsible for 20% of emissions[2] (EEA, 2015). Moreover, the sector has shown a 21% growth in emissions since 1990 (EEA, 2014). Road vehicles are the main contributors to GHG emissions within the transportation sector. Reducing emissions from transportation is thus a key element in any comprehensive strategy to reduce global GHG emissions.

Effective medium- and long-term solutions require the integration of a climate change reduction strategy in public policies, to enable new ideas on how to transport people and goods, how to provide energy, and how to build cities (EEA, 2015). Specifically, adapting a transportation infrastructure is difficult, because it involves different actors, ranging from vehicle producers and infrastructure managers to passengers. The European Commission's Transport White Paper (EC, 2011) aims to outline strategies for changing people's behavior by applying a "fuel-efficient driving style and making use of ICT" to decrease business travel.[3] Innovations in transportation and in technologies, such as the transition to electric cars or more investment in modern public transportation networks, are the means to social and economic progress. However, technological improvements are expensive. According to European Commission[4] estimates, for the next 40 years, it would be necessary to invest an additional EUR 270 billion per year in order to have "low carbon" EU energy and transportation.

Transportation-related GHG data extracted from emissions inventories are the primary source for (i) elaborating environmental accounting tables, which are required to perform statistical analysis, and (ii) research exploring the potential of engine and vehicle technologies, fuel developments, and market and travel demand, and examining the impact of policies to promote changes in the road transportation of the future. However, in order to design effective policies for reducing transportation emissions or to devise adequate mobility plans, there is an increasing need to produce reliable emissions inventories, which in turn depend on appropriate uncertainty assessment. Uncertainty in measurement can stem from several factors: poor air pollution monitoring systems, inadequate traffic models, especially when future projections in space and time are considered, bad expert judgments in choosing model parameters and emission factors, and other objective and subjective factors related to the assessment models. However, uncertainty in developing appropriate transportation policy may also be related to the choice of the GHG emissions price, which affects the results of policy option assessment, for instance in a cost-benefit analysis framework (Nocera and Tonin, 2014; Nocera et al., 2015). The validity of the assumptions underlying the physical quantities of emissions and their economic value strongly influences transportation policies related to GHGs. To our knowledge, only a few studies in the literature deal explicitly with uncertainty analysis regarding GHG emissions. For example, Mensink (2000) implemented two emission validation methods to test the precision of the emission factors and the accuracy of modeled traffic flows and to determine the completeness of the inventory, such as coverage of all sources. Singh et al. (2008) tried to reduce uncertainties in the estimation of GHG emissions by considering the issues related to activity data, such as proper apportionment of the fuel types (i.e., diesel and gasoline) across different categories of vehicles and other sectors (such as railways, take-away sales, etc.) in India. Puliafito et al. (2015) proposed a procedure to improve the inventory of emissions with high resolution, based on a geographic information system for the transportation sector in Argentina. Valenzuela et al. (2017) developed a model to quantify uncertainty of the input parameters related to the marginal abatement cost curve in the transportation sector in Colombia. Alam et al. (2017) estimated carbon dioxide (CO_2) emissions from road transportation at the vehicle category level in Ireland, using an improved bottom-up estimation methodology and various sources that provided useful disaggregated data (such as mileage and fleet disaggregation, speed parameters, and mean trip distance).

In this paper, we tackle the issue of uncertainty in GHG emissions from road transportation, combining data from different sources in order to increase the reliability of the uncertainty measure. Moreover, we propose an original method, an insurance-based approach enhanced through Monte Carlo simulation, to improve the uncertainty estimates. Although the case study is based on one Italian region (Piedmont), the methodology and analysis could be applied wherever a regional emission inventory is available. GHG emissions are measured by the global warming potential[5] (GWP) indicator. The paper specifically investigates how GHG emissions estimates are affected by uncertainty, both at the stage of compiling hybrid accounting tables and at the stage of using this information to address a specific policy question. The uncertainty question is approached using a conceptual model (Section 2) that sets out different methods, depending on the stage at which data are considered: the estimating procedure, data analysis, and data use. All the stages of the conceptual model are described and assessed: uncertainty in data production is managed by using an insurance-based approach enhanced through the Monte Carlo method (Section 3.3); uncertainty in data analysis is addressed by integrating emission estimates with regional energy balances (Section 3.4); uncertainty in tackling a specific policy question is reduced by further integrating ad hoc transportation statistics in a quantitative assessment procedure (Section 3.5). The policy question relates to the indirect impacts generated by economic activities: transportation itself is linked to those production sectors that need their products to be delivered over a long distance, thus generating additional GHGs in the transportation sector. In sustainability policies, this is not a secondary issue. Finally, the outcomes of the tested hypotheses are compared (Section 4) and discussed (Section 5).

2. Theoretical background

Disciplines that need information about the emission of pollutants into the atmosphere make use of measurements. A common source of such measurements is air pollutant inventories, which are mostly compiled at the national level, although in some countries there are also regional inventories. In Italy, the European Directive 2008/50/EC on ambient air quality and cleaner air for Europe was introduced into the national legislation by Legislative Decree no. 155 (13th August 2010). The legislation states that the whole country and its regions (and autonomous provinces) should develop their emissions inventories, with adequate spatial and temporal resolution.

The CORe INventory AIR emissions (CORINAIR) system is the calculation method approved by the European Environment Agency (EEA) to assess emissions. CORINAIR adheres to the IPCC guidelines, which have been used globally by environmental protection agencies for national and regional assessments. According to the IPCC Guidelines (2006), a compiler builds a decision tree in order to select the appropriate methodology: (i) Tier 1 employs a very basic methodology that uses default data; (ii) in Tier 2, both the methodology and the need for data become more demanding; (iii) Tier 3 implies an increase in model complexity and data requirements.

To analyze uncertainty, the models used can be based on simple

[2] Excluding land use, land-use change, and forestry (LULUCF).

[3] E.g., teleworking and virtual meetings.

[4] http://ec.europa.eu/clima/policies/strategies/2050/index_en.htm.

[5] The global warming potential (GWP) allows comparison of the global warming impacts of different gases. As an example, the GWP measures how much energy the emissions of 1ton of a gas will absorb over a given period of time, relative to the emissions of 1 t of carbon dioxide (CO_2) (see https://www.epa.gov/ghgemissions/understanding-global-warming-potentials).

arithmetic multiplication of activity data (AD) and an emission factor (EF), or they may be more specific and more complex. According to the tier that is applied, a different typology and degree of uncertainty can arise.

Uncertainty analysis deals with random errors that can depend on the system's intrinsic variability, on the finite sample size of available data, on the random components of measurement error, or on the subjectivity of the expert judgment (IPCC, 2006). Uncertainty estimates should be quantified for EF, AD, and all the estimation parameters used. They should also be quantified for the trend estimates. The two main statistical concepts used are the probability density function (PDF) and the confidence interval. The calculation of the random errors adopts the conventional 95% confidence interval. To assess uncertainty, it is possible to use empirical data, expert judgment, or a combination of both. In the IPCC guidelines, the possible typologies of PDF are listed, following Frey and Rubin (1991). Among these, the most appropriate PDFs are the normal distribution, if the range of uncertainty is small and symmetric relative to the mean, and the uniform distribution, when there is an equal probability of all values or for representing expert judgment if an upper and lower boundary can be specified. The IPCC identifies two main methods to assess uncertainties. The first uses simple error propagation equations; the second uses Monte Carlo or similar techniques. The Monte Carlo method is the technique most commonly used by the environmental agencies responsible for compiling GHG inventories.

Uncertainty is a common concept in many disciplines; it entails measurement, test, methodology, and data. Tonin et al. (2016) reviewed the main scientific literature to investigate how the different disciplines handle uncertainty and what can be learned from various scientific fields to address uncertainty, specifically for improving GHG inventories. They found that, when moving from physical sciences to social sciences and decision-making, the analysis of uncertainty expands from (i) quantitative, mainly statistical methodologies, aimed at improving the detail of the data, to (ii) flexible open approaches, aimed at integrating quantitative and qualitative information. Finally, they developed an approach to summarize the main results: a use-chain model (see Fig. 1) to interpret how to deal with uncertainty, simultaneously considering the purpose and the final users.

The three blocks shown in Fig. 1 summarize the logical reasoning tested and applied in this paper.

- The first block comprises “data production.” Most physical science applications are designed to produce reliable data, and most of the methods are employed to enhance sampling and classification. In the present case, we extract data from the inventory to which we associate the relative uncertainty, using an insurance-based approach enhanced through the Monte Carlo method (Section 3.3).
- The second block comprises “data analysis.” Transportation is among the disciplines that need data on emissions for analysis. In this case, uncertainty is reduced by providing information derived from additional and complementary datasets, rather than concentrating on statistical methodologies. We build a hybrid environmental accounting table that can be used for multiple purposes, and we aim to reduce uncertainty by integrating data extracted from energy balances (Section 3.4).
- The third block consists of “data use.” Research is applied for a specific policy purpose that has to be explicitly defined. Information to reduce uncertainty can be expanded, not only quantitatively but also qualitatively, by employing a variety of techniques, including also participatory approaches. In the present case, we address the policy question of assessing direct and indirect emissions from economic sectors by integrating road freight transportation statistics (Section 3.5).

The first two blocks shown in Fig. 1 are developed and tested through three hypotheses. A graphical summary of the procedure is shown in Fig. 2.

The quantitative basis for **Data Analysis** is represented by a hybrid accounting module (Section 3.2) that links economic data and air emissions in the same table. The estimates reported in the hybrid accounting module change according to the applied procedure to reduce (or not reduce) uncertainty (**Data Production**). Table 1 synthesizes the hypotheses tested in this paper.

One important difference between data production and data analysis is that the former applies to the estimates provided by the inventory and can be employed in a vast array of tools. The latter depends on the tool in which inventory estimates are employed: it makes sense to integrate energy balance data in the hybrid accounting modules tool, but it probably would not make sense in other tools (e.g., air quality deposition and dispersion modeling). Hybrid accounting modules can still be employed for multiple uses, including helping to provide answers to a variety of policy questions.

The third block of Fig. 1 is tested by introducing a specific policy question (**Data Use**). Air emissions may be wrongly ascribed to the transportation sector, because products produced in some places are consumed in others. It is thus important to determine which sectors export the most: direct and indirect emissions will be attributed to these sectors, whereas indirect emissions are those generated by transportation activities. This is important information for any policy maker who hopes to deal with the issue of air emissions due to transportation. Fig. 3 illustrates how the previous hypotheses are linked to information concerning the specific policy question.

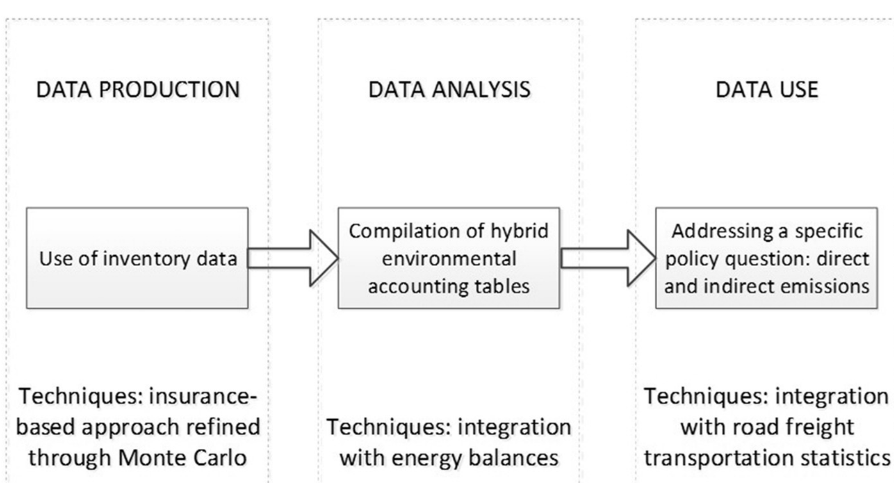

Fig. 1. The use-chain model applied to road transportation to reduce uncertainty.

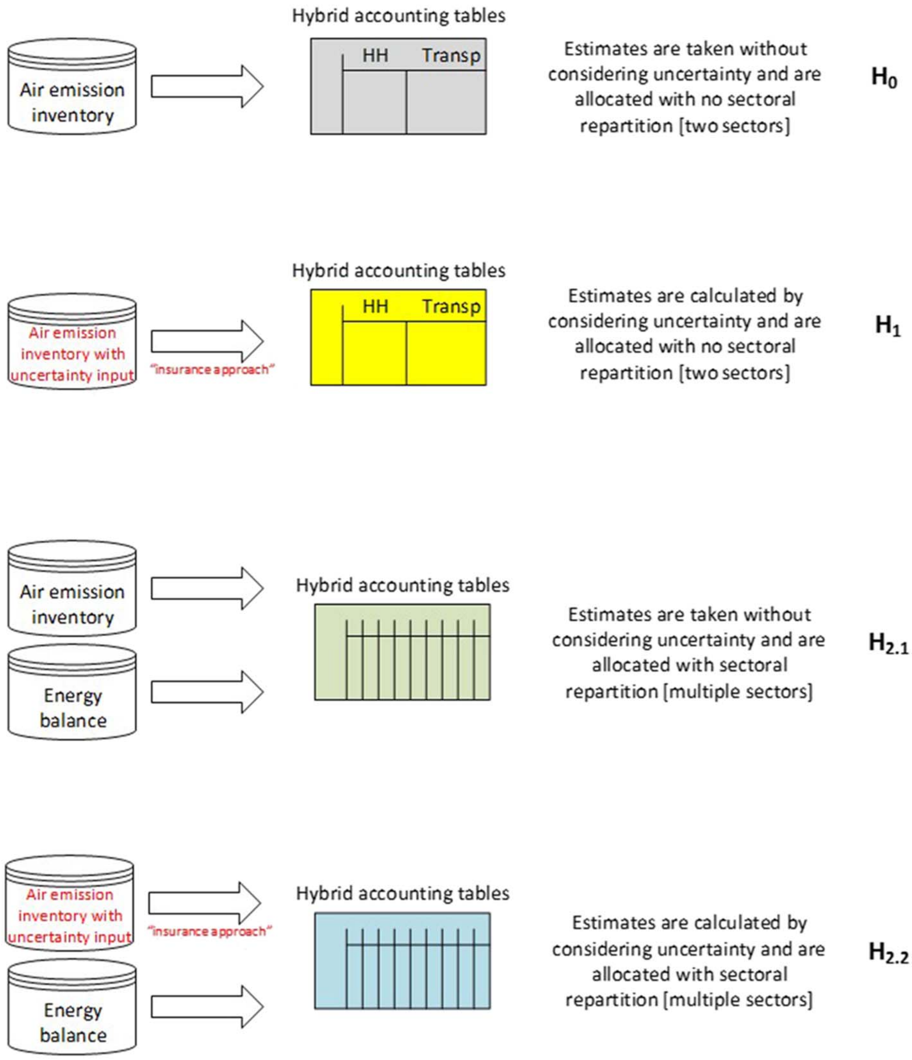

Fig. 2. Graphical summary of hypotheses and methods.

Table 1
Setting of the hypotheses according to the use-chain model.

Hypothesis 0	Accounting module where uncertainty has not been considered
Hypothesis 1	Accounting module with uncertainty reduction, considering an insurance-based approach enhanced through the Monte Carlo technique (**Data Production**)
Hypothesis 2.1	Accounting module with uncertainty reduction, considering only integration with the energy balance data (**Data Analysis**)
Hypothesis 2.2	Accounting module with uncertainty reduction, considering an insurance-based approach enhanced through the Monte Carlo technique and integration with the energy balance data (**Data Analysis**)

3. Materials and methods

We aim to provide a multiscale method to deal with uncertainty in estimating GHG emissions from road transportation using a use-chain model (Tonin et al., 2016). Accordingly, we use the data contained in the inventory of emissions from road transportation compiled for the Piedmont Region, disaggregating them employing hybrid accounts, as input data (3.1 and 3.2). Then, we revise the measure of uncertainty provided in the inventory with an insurance-based method improved through Monte Carlo simulation (3.3). Next, we test an incremental process of data integration using different sources (energy balances and road freight transportation statistics) to explore the hypotheses illustrated in Fig. 2.

3.1. The Piedmont Region and the regional inventory

This work is based on the road transportation industry in the Piedmont Region of north-western Italy. The industry is the backbone of the economy, and it holds a monopoly in the automobile industry and in road vehicles (i.e., trucks, buses, etc.). Moreover, the transportation sector is well advanced in the region; for example, the rail network, built mostly in the second half of the last century, is one of the densest in Europe, and Piedmont has the longest total road network (31,000 km) of any region in Italy.

We chose this case because the inventory in Piedmont (henceforth 'the inventory') has existed for longer than in other regions, and it reports information (including uncertainty) that other regional inventories do not contain. The EMEP-CORINAIR[6] inventory, now known as the EMEP/EEA air pollutant emission inventory guidebook, has been compiled since 2001 by the Regional Directorate of Environment, Government, and Land Protection, which is also active in the inter-regional network INEMAR (http://www.inemar.eu/xwiki/bin/view/Inemar/).

The inventory is created mainly using a bottom-up approach; data are collected and analyzed at the most detailed administrative level, the municipality level. The top-down approach is used if detailed information at the local level is not available or to validate the

[6] European Monitoring and Evaluation Programme (EMEP).

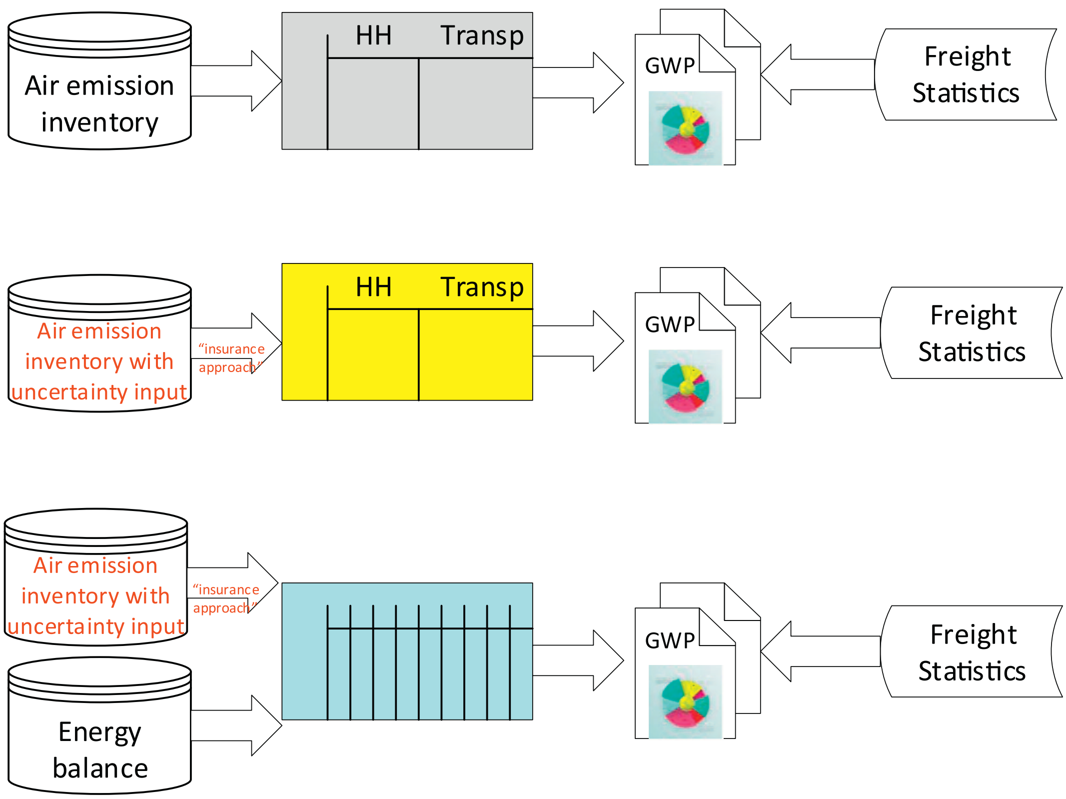

Fig. 3. The application of the hypothesis to a specific policy question.

information derived from the bottom-up approach. The top-down information is disaggregated to municipal level using appropriate proxies.

The estimation procedure has been greatly improved and updated, while generating new information. The regional inventory records data according to the SNAP (Selected Nomenclature for Air Pollution) classification. It collects data from 11 macro-sectors,[7] 75 sectors, and 430 activities. The recorded pollutants are methane (CH_4), carbon monoxide (CO), carbon dioxide (CO_2), nitrogen dioxide (N_2O), ammonia (NH_3), volatile organic compounds (VOCs), oxides of nitrogen (NOx), sulfur dioxide (SO_2), and particulate matters (PM10 and PM2.5).

In this application, we consider only the GHGs, namely carbon dioxide, methane, and nitrous oxide. We calculate the global warming potential (GWP) by using the following coefficients: 1 for CO_2; 310 for N_2O; and 21 for CH_4 (European Commission, 2009).[8]

Our analysis is related to road transportation (Macrosector 7), whose emissions have been calculated as linear emissions to the atmosphere. The first type is related to emissions from vehicles on major routes (e.g., freeways and highways), and emissions are estimated using a registry (the Road Information System) that captures and processes all information on the roads within the region. Data on average daily traffic are divided into heavy and light vehicles and refer to an average day, ignoring any differences according to the season or day of the week. Information provided by the regional fleet is used to split the average daily traffic between light duty and heavy duty vehicles. The air emissions derived from vehicles traveling within towns are calculated using the data on registered vehicles, their mileage, and their average speed (provided by the organization for public transportation in Turin, the Telematic Technologies for Transport and Traffic in Turin [5T]). These data feed three models: (i) the traffic model allows the average speed of vehicle flow[9] to be calculated, (ii) the emissions model provides the emission factors[10] as a function of the vehicle fleet, of the flows calculated by the traffic model, and of the environmental conditions (e.g., humidity and temperature), and (iii) the dispersion model allows calculation of the concentrations of pollutants in the atmosphere, known emission factors, and weather conditions (e.g., wind and rain). What matters for the inventory is the outcome of the emissions model.

An important element is that the inventory provides uncertainty coefficients for activity data (AD) and emission factors (EF), which range from 1 (when estimates are based on a large number of measures in a large number of installations representing the whole sector) to 0.2 (when, for example, estimates are based on engineering calculations based solely on assumptions). Uncertainty coefficients have been attributed to each of the 430 activities at the most accurate administrative level (i.e., municipality).

3.2. Hybrid accounts as the basic methodology to frame economic and environmental data: Hypothesis 0

Environmental accounts are satellite modules that can be added to core national accounts in order to integrate environmental data with current economic data. Hybrid accounts, the main example of which is the National Accounting Matrix including Environmental Accounts (NAMEA), have the advantage of integrating environmental and economic data, without converting all into monetary terms. Applications of NAMEA-type modules at sub-national levels already exist (Dalmazzone

[7] The 11 macro-sectors are: 01 Public power, cogeneration and district heating plants; 02 Commercial, institutional and residential combustion plants; 03 Industrial combustion; 04 Production processes; 05 Extraction and distribution of fossil fuels; 06 Solvent use; 07 Road transport; 08 Other mobile sources and machinery; 09 Waste treatment and disposal; 10 Agriculture; 11 Nature.

[8] Since we are compiling hybrid accounts, we are using the Eurostat manual on air emissions as a reference for the GWP.

[9] The traffic model is based on the geometry of the road network and on the matrix Origin–Destination, which reports the average daily traffic for different road sections.

[10] Emission factors are the amount of the pollutant emitted by each vehicle category per unit of time or space.

and La Notte, 2013; La Notte and Dalmazzone, 2012; Dalmazzone and La Notte, 2009).

Thanks to NAMEA, it is possible to connect air emissions to the activity that generates them, an approach that allows economic data and emissions to be correlated. At local level, economic data are drawn from the register of active firms (ASIA[11]) that integrates national administrative archives with other sectoral registers and with statistical surveys available from the Italian National Institute of Statistics (ISTAT). ASIA provides data on local units and numbers of employees. Air emissions data are taken from EMEP-CorinAIR (Section 3.1).

One methodological problem encountered when combining datasets from different sources is reclassification. Emissions inventories are classified according to the SNAP classification, which is based on production processes, while economic data follow the NACE (Nomenclature statistique des activités économiques dans la Communauté européenne) classification, which relates to economic activities. There are International Guidelines (Eurostat, 2015) that attempt to establish a clear correspondence between SNAP and NACE, but, in some cases, one-to-one matching is not possible. Transportation is one such case. Our application contributes to this still-debated issue. According to the SNAP classification, data from Macrosector 7[12] (Road Transport) were extracted, and only air emissions for CO_2, N_2O, and CH_4 generated by road transportation are considered in this paper.

In Hypothesis 0, we report the data when uncertainty has not been considered, attributing these data to one NACE economic sector and to households as follows: the transportation sector (corresponding to sector 49 according to NACE rev. 2), which includes light duty vehicles (< 3.5 t), heavy duty vehicles (> 3.5 t), gasoline evaporation from vehicles, and automobile tire and brake wear; and the households sector, which includes passenger cars, mopeds, and motorcycles [< 50 cm^3] and motorcycles [> 50 cm^3].

The reference table is reported in the Supplementary material I (Table S1).

3.3. Insurance-based approach to insert uncertainty in data production: Hypothesis 1

All emission estimates contain uncertainties, and a reliable methodology is needed to deal with them. Borrowing an approach from the insurance industry (Marland et al., 2014), we apply a methodology with the twofold aim of dealing with and simultaneously reducing uncertainty. In particular, Marland et al. proposed an additional risk charge to the cost of CO_2 emissions to include measurement errors, uncertainties in the calculation methods, and the probability of the occurrence of unusual events. This additional risk factor[13] is obtained by multiplying the percentage of uncertainty by the carbon price per ton, so that the price of carbon released and the risk charge can be calculated to obtain the adjusted valuation of the emissions.

The IPCC guidelines (1996, 2006) recommend the Monte Carlo technique, classical analysis, or the help of experts to estimate the ranges of uncertainty in order to obtain the conventional 95% confidence interval for the probability distribution function. Thus, in the present work, an insurance-based method improved by the Monte Carlo technique was used. This technique has the specific advantage of being capable of dealing with a situation in which it may be difficult to combine large uncertainties related to a different probability distribution. Following IPCC Guidelines (2006), we selected random numbers from each AD and EF probability distribution, and then the total emissions are calculated 10,000 times by 10,000, varying input parameters according to their average and variance, to obtain the probability distribution of total emissions. The simulated distribution function and therefore the relative uncertainty can be calculated, as measured by the standard deviation.

In this study, the value of X, represented by the emission of CO_2, N_2O, and CH_4 from economic activities in the Piedmont Region, is represented by:

$$X = X\ \text{measured} \pm (X\ \text{measured} * s\%),\ \text{with}\ X \in [a, b] \tag{1}$$

where X measured is the emissions measurement available (source: Piedmont Region). s% is the conventional uncertainty, expressed as an emissions percentage (source: Piedmont Region).

Knowing the distribution of X, we can express uncertainty as the confidence interval constructed around the measurement associated with a given probability. Typically, the interval is used with coverage by a factor K:

$$X - K*X*s\% \le X \le X + K*X*s\% \tag{2}$$

In this research, the range of variation (starting from s%) is interpreted as the 95% confidence interval of the variables. We assume K = 1.05 for a uniform distribution; K = 1.96 for a normal distribution; and K = 2.23 for a Student's *t*-distribution. The 90%, 95%, and 99% intervals are typically adopted in statistical analysis, 95% being the most commonly used (Weerahandi, 1993).

When probability distributions are used, variables can assume different values with their associated probabilities. The choice of the appropriate probability distribution depends on the specific characteristics of the environmental phenomenon that is to be studied. In particular, it relies on the emissions category, source, and intensity (Zhao et al., 2011). Usually, the total amount of emissions includes different sources, each with specific parameters and with a specific range of distribution and uncertainty. The most common probability distributions used in previous analogous studies include uniform, normal, and Student's t-distribution (McNail and Frey, 2000). For example, pollutants such as SO_2 behave in a uniform manner, and their uncertainty levels are relatively low. Student's *t*-distribution is commonly applied when it is important to consider the tail of the distribution of extraordinary events (i.e., local air pollution), but in general air emissions data tend to be normally distributed.

Total annual emissions distribution is used to calculate descriptive statistics and specific measures such as median, average, minimum value, maximum value, and range of variation, as well as additional and more explanatory information, such as standard deviation in absolute and in percentage in relation to the average (Dev. Std./Media ∗ 100). The values calculated by employing the insurance-based method enhanced through the Monte Carlo technique are reported in the Supplementary Material (Table S2).

Finally, to conclude our empirical work, we build the partition function to identify the level of overall annual emissions with a certain confidence interval, namely the emission value at risk, in line with one of the best-known and most frequently used measures of the financial sector, designated the value at risk (VaR) (Linsmeier and Pearson, 2000). This metric is a measure of risk applied to financial investments that, according to Morgan (1996), “quantify the worst expected loss under normal market conditions over a specific time interval at a given confidence interval. In other words, the VaR estimates how much people can lose with x% probability over a pre-set horizon.” Following the same principle in the context of emissions policies, the question that policy makers should ask is: What is the highest level of emissions in this territory (or economic sector)?

In other words, the emission value at risk, in our context, measures the level of emissions of a territory (or economic sector) that can

[11] ASIA stands for Archivio Statistico delle Imprese Attive.

[12] It includes seven sectors (passenger cars, mopeds, and motorcycles [< 50 cm^3], motorcycles [> 50 cm^3], light duty vehicles [< 3.5 t], heavy duty vehicles [> 3.5 t], gasoline evaporation from vehicles, and automobile tire and brake wear) and six activities (related to route types and their wear).

[13] This additional risk factor is similar to the risk charge that insurance incorporates in addition to the premium paid, in order to estimate future uncertainties. It includes the discounted value of future payments. This risk charge, which in turn was inspired by a work by Rubin et al. (2009), comprises both data variability and the likelihood of rare events that can determine higher costs.

Table 2
Emission VaR for CO_2 for a given area and 13 sectors (yearly value).

Percentile	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7	Sector 8	Sector 9	Sector 10	Sector 11	Sector 12	Sector 13	Total CO_2
1.0	307.0	56.9	638.3	68.5	149.6	85.5	11.3	218.0	167.2	878.6	96.2	3.9	3465.6	6146.7
0.9 (emission VaR)	**236.0**	**43.7**	**490.6**	**52.7**	**115.0**	**65.7**	**8.7**	**167.5**	**128.5**	**675.3**	**73.9**	**3.0**	**2663.6**	**4724.2**
0.8	222.3	41.2	462.2	49.6	108.3	61.9	8.2	157.8	121.0	636.2	69.7	2.8	2509.5	4450.9
0.7	213.0	39.4	442.8	47.5	103.8	59.3	7.9	151.2	116.0	609.5	66.7	2.7	2.404,0	4263.7
0.6	204.4	37.9	425.0	45.6	99.6	56.9	7.5	145.1	111.3	585.0	64.1	2.6	2.307,3	4092.3
0.5 (mean)	*196.9*	*36.5*	*409.3*	*43.9*	*95.9*	*54.8*	*7.3*	*139.8*	*107.2*	*563.4*	*61.7*	*2,5*	*2.222,0*	*3941.0*
0.4	189.4	35.1	393.7	42.3	92.3	52.7	7.0	134.5	103.1	542.0	59.3	2,4	2137.7	3791.5
0.3	181.5	33.6	377.2	40.5	88.4	50.5	6.7	128.8	98.8	519.3	56.9	2,3	2048.2	3632.7
0.2	171.9	31.8	357.4	38.4	83.8	47.8	6.3	122.1	93.6	492.0	53.9	2,2	1940.6	3441.9
0.1	158.7	29.4	329.8	35.4	77.3	44.2	5.9	112.6	86.4	454.0	49.7	2,0	1790.8	3176.1
0.0	73.0	13.5	151.7	16.3	35.6	20.3	2.7	51.8	39.7	208.9	22.9	0,9	823.8	1461.1

increase in a specific interval of time, with a given probability, as a consequence of different activities. The main factors of emission VaR are the interval of time in which emissions are evaluated, and the interval of confidence; the choices made by analysts regarding these factors determine the results of the emission VaR model.

Emission VaR is just a number that gives an estimate of the extent of risk in a certain territory. It is measured in emissions units. This makes the value very easy to understand and interpret and to use in further analyses, which is one of its biggest advantages. In Table 2, we present a possible distribution function extracted from a Monte Carlo simulation with normal distribution for the expected CO_2 in a given area for the 13 different sectors within one year.

For the application undertaken in this paper, we calculated the emission VaR at 90% (i.e., 10% risk).

3.4. Integration of energy balance datasets to reduce uncertainty in data analysis: Hypotheses 2.1 and 2.2

Unlike in Hypothesis 0, in Hypothesis 1 we consider uncertainty by applying the insurance-based method enhanced through the Monte Carlo technique. However, although uncertainty is being explicitly considered, the limit of Hypothesis 1 remains the attribution of transportation air emissions to a single economic sector and households.

A sophisticated statistical technique to reduce uncertainty is not of value if the initial allocation is not correct and fails to represent reality. Within other economic sectors, in fact, transportation is indeed a secondary or ancillary activity. In order to make the data on emissions more reliable (and thus to reduce uncertainty), it is important not to allocate to the transportation sector those emissions that are associated with the demand for transportation stemming from other economic activities. Regional Energy Balances[14] offer a way to solve this issue, because they provide, for each economic activity, the consumption of diesel and gasoline that may be used to distribute road transportation emissions across industries (Eurostat, 2009). Other fuels such as natural gas (0.1%) and liquefied petroleum gas (LPG) (0.4%) are not considered in the analysis, because they represent a small percentage of the total energy consumption, they can also be used for heating and hot water in buildings, and their consumption thus cannot be attributed solely to transportation.

By estimating the percentage of total fuel consumption in all economic sectors that can be attributed to their demand for transportation, it is possible to estimate the emissions generated in the manufacturing, building, and transportation sectors that should actually be attributed to other economic activities.

Using in turn the energy balance data integration (Hypothesis 2.1), and a combination of an insurance-based method enhanced through the Monte Carlo technique and energy balance data integration (Hypothesis 2.2), we consider 13 sectors for the analysis of indirect emissions, with a view to reducing the uncertainty associated with estimated emissions directly attributable to the transportation sector. Hybrid accounting tables showing the specific analysis implemented are presented in the Supplementary material I: when comparing the two-sector data (S1 and S2) with the multiple-sector data (S3 and S4), it is immediately clear how the weight of the transportation sector in total GHG emissions changes; accounting for indirect emissions (S3) reduces uncertainty more than introducing uncertainty coefficients to the inventory estimates (S2).

The best option is, of course, to both consider the multiple sectors and account for the uncertainty coefficient (S4). This stage of the application lies in the second block ("data analysis") shown in Fig. 1. In fact, at this stage, the purpose of addressing data uncertainty is not to generate reliable data (which is attributable to "data production") but to build a tool that can help analysts, researchers, or general users to make better-informed decisions. The purpose is not yet set: there is a variety of uses for hybrid accounting tables, which can range from simple descriptive statistics to more complicated macroeconomic predictive models.

3.5. Direct and indirect emissions: integrating road freight statistics in data use

Direct emissions have been discussed above. In Hypothesis 1, they are all attributed to the transportation sector and to households; in Hypotheses 2.1 and 2.2, they are attributed not only to transportation but also to those economic sectors for which transportation is a secondary or ancillary activity. In dealing with indirect emissions, it is necessary to focus on the transportation economic sector and to consider the companies or sectors for which commodities are transported. Any economic activity has an environmental impact, not only at the stage of production but also at the stage of delivery to the buyer. In this paper, we explore the direct and indirect road transportation emissions of GHGs in Piedmont, with a view to determining how uncertainty affects those estimates.

ISTAT publishes road freight statistics annually. One important indicator is tons per kilometer (tkm), which is the product of the quantity carried (tons of good/s) and the kilometers traveled. This indicator is available for groups of products and concerns heavy vehicles ($>$ 3.5 t). The tkm is the indicator by which emissions from road transportation can be broken down by economic activity; this makes it possible to discover the additional quota of emissions generated by the final distribution of goods/commodities. In our application, we consider the tkm that originate in the Piedmont and whose destination is Italy (including Piedmont) or other countries. There are eight major groups[15] of

[14] http://www.efficienzaenergetica.enea.it/politiche-e-strategie-1/politiche-e-strategie-nelle-regioni/sistemi-informativi-energetici-regionali/bilanci-energetici-regionali/.

[15] The eight groups are: 1) agricultural, hunting and fishing products; food, beverages and tobacco; 2) coal, coke, crude oil; refined petroleum products; natural gas; 3) ores;

Table 3
Allocation of transportation emissions as indirect emissions to other economic sectors.

Transported good	Tons transported	Ton-kilometers (tkm)	% of totals
1. Agriculture, forestry, fishing; food, beverage and tobacco	15,983,255	146,000	12.20
2. Fossil fuels, coke and refined petroleum products; natural gas	4,431,446	40,000	3.30
3. Ores; other mining, metal products; building materials, ceramic products	72,451,994	660,000	55.20
4. Chemical products, rubber and plastic products	4,599,804	42,000	3.50
5. Textiles, wearing apparel and leather and related products; wood, furniture, paper and printing	4,314,613	39,000	3.30
6. Fabricated metal products, electrical equipment and general machinery; motor vehicles, trailers, semi-trailers and other transport equipment	4,334,977	39,000	3.30
7. Secondary raw materials, waste; other goods	22,002,548	200,000	16.70
8. Mail, boxes, container, pallets, etc.	3,177,597	29,000	2.40

goods/commodities that can be attributed to their producing economic sectors (properly grouped) and for which the tkm can be calculated, starting from the annual statistics made available by ISTAT. Table 3 presents the total transported goods (in tons) divided by the average distance, in order to obtain the tkm.

The percentages of emissions reported in Table 3 highlight the economic weight of transportation for the different economic activities. This is a starting step for introducing an analysis of indirect emissions.

4. Results

The outcomes obtained so far may be analyzed from the perspective of the policy implications. This refers to the way in which the application of the two hypotheses affects the results of the accounting tables in the absence of any particular policy question (Section 4.1), and thus highlights the sensitive issues to be alert to when considering uncertainty itself. The policy implications are also explored through a specific policy question (4.2), in order to check to what extent uncertainty can, in practice, affect the information delivered to final policy makers and policy analysts.

4.1. Results of Hypothesis 0 compared with Hypothesis 1 and Hypothesis 2.2

Our results highlight the importance of acknowledging not only the different assessment used for the diverse pollutants examined when uncertainty is taken into account but also the way in which uncertainty is quantified.

Fig. 4 and b (based on the data reported in Tables S2 and S4 in the Supplementary Material[16]) clearly show that, when moving from a two-sector to a multiple-sector perspective, the estimated emissions are almost halved. An integration-based data analysis can affect results (and eventually reduce uncertainty) more than the pure statistical techniques applied to raw estimates. In particular, Fig. 4a shows the outcomes related to Hypothesis 1 (see Table 1) for a two-sector perspective, and Fig. 4b shows the results of Hypothesis 2.2 for a multiple-sector perspective. It should be noted that, in both figures, Hypothesis 0 stands for the "uncertainty not considered" accounting module.

The most important implications of the analysis are that data without uncertainty show almost a 30% variation when moving from a two-sector to a multiple-sector assessment. This variation suggests that any uncertainty calculated on the two-sector perspective starts from a weak initial dataset, and any reduction of the uncertainty (variation of 43% recorded with the normal distribution or of 55% recorded with Student's *t*-distribution) is going to be biased. On the other hand, the multiple-sector perspective is based on a wider range of primary data (not only data on emissions but also energy) and allows disaggregating initial data and thus correcting the uncertainty linked to the initial data bias. The multiple-sector approach shows, in fact, smaller variations due to uncertainty (variation of 16% with the normal distribution or of 21% with Student's *t*-distribution).

A rough allocation to the transportation sector (as in Hypotheses 0 and 1) yields an overestimate. However, a better estimation, closer to reality, can be reached by allocating emissions correctly to transportation and other sectors (Hypothesis 2.2). Specifically, the value of GWP for the road transportation sector (Fig. 5), when uncertainty is not considered at all and when no data integration is performed, is about 4144 kilotons (kt) (Hypothesis 0). However, if the emission inventory and uncertainty are taken into account, a much higher value for GWP (5933 kt) is obtained (Hypothesis 1). It is important for uncertainty to be part of the equation, but it is also important to make an accurate sectoral allocation. Thanks to the regional energy balance, the uncertainty of emissions allocation can be reduced. In the case of road transportation emissions corrected through energy balance, the GWP without uncertainty is lower (2892 kt) (Hypothesis 2.2) than the GWP calculated by reference to the inventory alone. This value increases when uncertainty is taken into account (3579 kt), but remains lower than the estimates based on the inventory alone. The common outcome is that accounting for uncertainty remarkably increases the initial value.

Overall, the results of our work emphasize that a statistical technique to account for uncertainty must be selected and correctly applied and, furthermore, that the database should be properly built and interpreted, including by integrating information from other sources. Our analysis demonstrates that it is possible to allocate emissions data to the transportation sector in a more appropriate and precise way, using different sources, and that this integrated information can reduce uncertainty.

4.2. Direct and indirect emissions under the different hypotheses

Any policy that aims to influence GWP must be focused not only on the emissions generated by the production process of any good but also on its delivery to the final consumer. Emissions due to production are direct emissions, while emissions due to delivery are indirect emissions. This analysis requires that the emissions generated by the transportation sector itself be attributed (according to the procedure explained in 3.4) to the producing sectors on behalf of which the good is transported.

Table 4 reports the estimates related to the secondary sector, for which we are able to use (thanks to ASIA) more disaggregated datasets. We compare the GWP calculated for the direct emissions generated from those sectors. Additionally, we find the sum of indirect emissions generated by transportation without uncertainty and with uncertainty.

For example, if we consider the manufacture of coke and refined

(*footnote continued*)
other mining, metal products; building materials, ceramic products; 4) chemical products; rubber and plastics; 5) textiles and clothing; leather products; wood and wood products; paper and paper products, furniture and other artifacts; 6) machines and mechanical appliances, electrical machinery and apparatus, television sets, communications equipment, transportation; 7) secondary raw materials, waste; other goods; 8) mail, containers, pallets, cargo within the removals, grouped goods, goods contained in a container.

[16] Please consider that CO_2 emissions are expressed in 1000 t (kt), because the amount of CO_2 is much larger than the amount of N_2O and CH_4. To consider tons of CO_2 instead of kt would not enable changes for the other two pollutants to be determined.

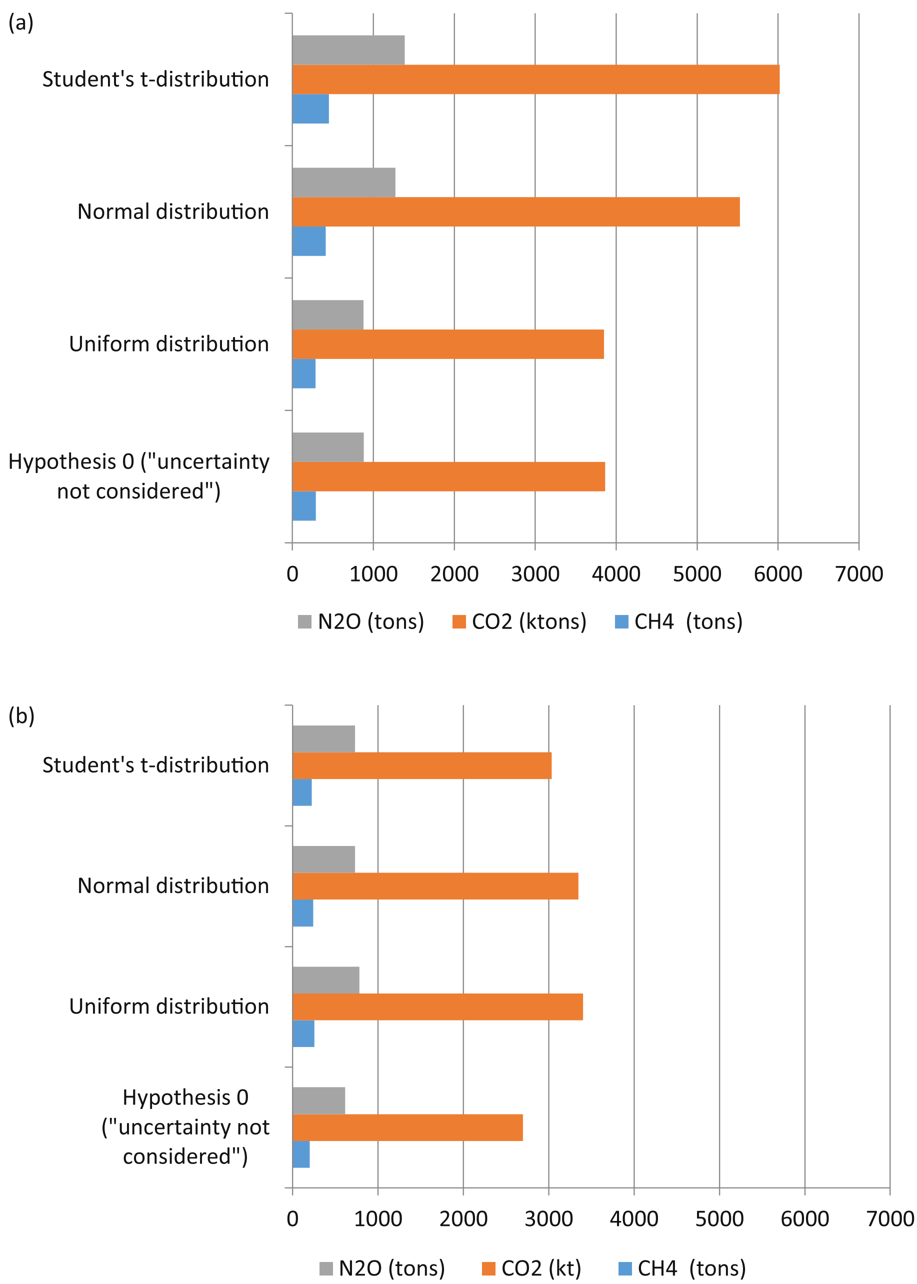

Fig. 4a. Road transportation emissions reported for Hypothesis 1 for a two-sector perspective. b. Road transportation emissions reported for Hypothesis 2.2 for a multiple-sector perspective.

petroleum products, the GWP referring to direct emissions is 2331 kt. If indirect emissions generated by transportation are added, and uncertainty is not factored in, the GWP estimate is almost doubled (4584 kt) under Hypothesis 1 and increased by more than two thirds (3904 kt) under Hypothesis 2.2. If direct and indirect emissions with uncertainty are considered, the estimate of GWP is much more than doubled under Hypothesis 1 and increased by five-sixths under Hypothesis 2.2. It should be noted that the information provided to the policy maker differs significantly if the indirect emissions are considered and if uncertainty is included. Moreover, it is important to properly account for uncertainty in order not to overestimate the impact itself; in fact, the outcomes from Hypothesis 2.2 are lower than those obtained by applying Hypothesis 1.

Fig. 6 shows the difference in the weight of GWP when only direct and then direct and indirect emissions are considered; the hypothesis depicted in Fig. 4 relates to the multiple sectors with a normal distribution. The decision not to take into account the uncertainty related to the direct emissions in calculating the GWP was intentional, since the effort lies in isolating the effect generated by the transportation sector. Fig. 6 illustrates the GWP related only to direct emissions.

5. Conclusions

Coping with uncertainty in research and policy activities is an ubiquitous challenge, which is all the more acute in relation to environment-related issues. Decisions are expected to be based on clear, measurable facts, but, in reality, missing data, measurement errors, and unpredictable processes give rise to several typologies, levels, and types of uncertainties.

Identifying, interpreting, analyzing, and reducing uncertainty is an extremely complex process that requires very good knowledge of the problem and appropriate methods and techniques.

Our research (Tonin et al., 2016) revealed that the current procedures for reducing uncertainty are progressively moving from more traditional statistical techniques to data integration, and in particular toward high-resolution spatial inventories (Bun et al., 2015). The

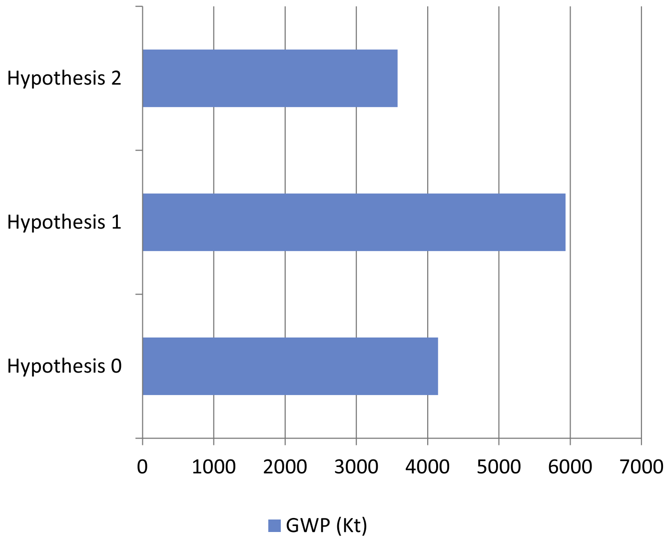

Fig. 5. Global warming potential calculated for road transportation.

present paper reports the original application of a use-chain model, in which the potential techniques to minimize uncertainty vary in relation to the purpose of the study and its stage of development.

The paper offers three different contributions to the present literature: methodological, empirical, and policy-related.

On the methodological side, we test and validate a conceptual framework (Fig. 1) that relates the techniques used to reduce uncertainty to the purpose of the study (i.e., data production, data analysis, and data use) and its stage of development (i.e., from setting an inventory to answering a specific policy question). The case study exemplifies how the use-chain model can be translated into practice and thus how the difference in the results obtained at each stage can be attributed to a different purpose and to a different approach. Moreover, considering specifically the statistical techniques employed to reduce uncertainty, we try to advance the use of an insurance-based method by integrating the Monte Carlo technique and by implementing emission value at risk (VaR) as a means of managing uncertainty in emissions policies.

We use the Monte Carlo method to quantify uncertainty and sensitivities; moreover, the simulation results are used to create the emission VaR to manage environmental risk, borrowing an instrument that is usually deployed in financial risk management. This value can de-

Table 4
GWP calculated as direct and indirect emissions with and without uncertainty.

Economic activities	GWP incl. direct emissions	GWP incl. direct and indirect emissions (1)		GWP incl. direct and indirect emissions (2)	
		Without uncertainty	With uncertainty	Without uncertainty	With uncertainty
Mining and quarrying; manufacture of other non-metallic mineral products; manufacture of basic metals	418.09	579.74	649.50	530.90	557.70
Manufacture of coke and refined petroleum products	2331.69	4584.76	5557.06	3904.02	4277.65
Manufacture of chemicals and chemical products; manufacture of rubber and plastic products	1339.16	1479.11	1539.51	1436.83	1460.04
Manufacture of textiles, wearing apparel and leather and related products; manufacture of wood, furniture, paper and printing	605.20	764.00	832.53	716.02	742.36
Manufacture, repair and installation of fabricated metal products, electrical equipment and general machinery; manufacture of motor vehicles, trailers, semi-trailers and other transport equipment	1685.53	1824.21	1884.06	1782.31	1805.31

Legend: (1) Hypothesis 1; (2) Hypothesis 2.2 considering the normal distribution.

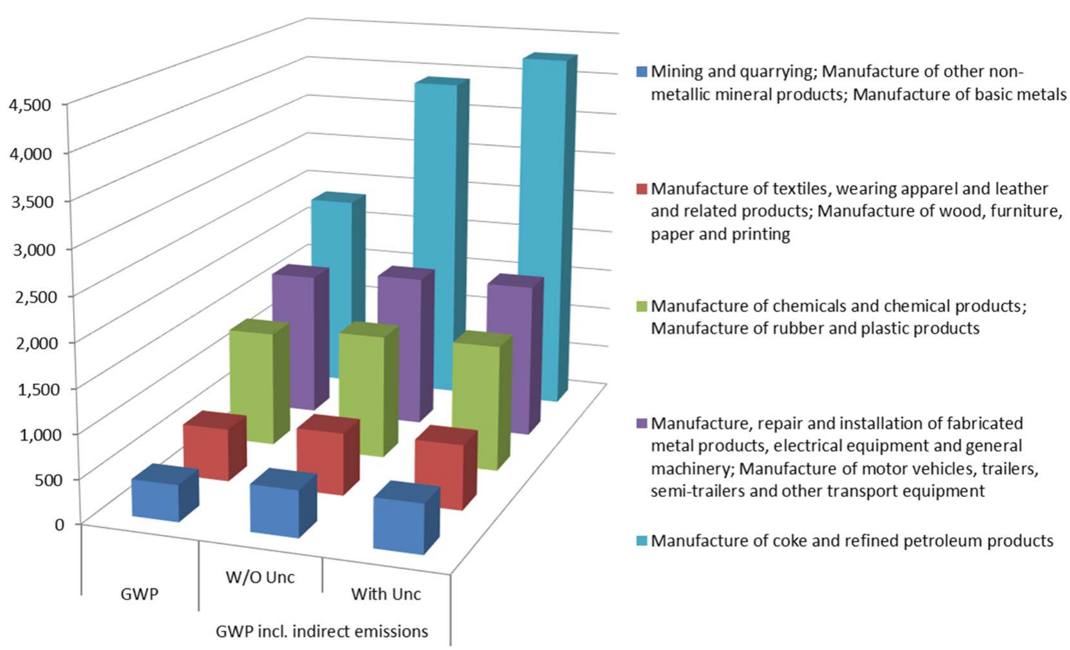

Fig. 6. Calculation of GWP with direct emissions only and with indirect emissions with and without uncertainty.

termine the maximum increase in the territory's level of emissions (or those of an economic sector) over a given period, with a given probability, as a consequence of changes in the activities giving rise to certain levels of emissions. Although the application of the emission VaR is far from being sufficient for practical environmental risk management, it is suggested that this experiment provides promising and innovative evidence.

The outcomes obtained prove the validity of the use-chain model because, in our case study, the first source of error (and thus uncertainty) was the standard practice of reporting data from only two sectors in the initial dataset. However sophisticated the statistical technique used, the assessment of uncertainty will always be biased. Moreover, we showed that when it is possible to integrate the data in the original emission inventory with other available sources of data, the assessment of uncertainty improves. In fact, we found that disaggregating sectors allows uncertainty to be reduced, even if not completely eliminated. This approach, however, does not apply necessarily to all environmental datasets. The appropriateness of the approach should be assessed case by case. However the use-chain model can be a useful tool to select options.

On the empirical side, we chose as a case study one of the most difficult typologies of emissions: road transportation. As already stated, it is impossible to attribute emissions from traffic to specific NACE economic activities. In our application, we propose a solution to this issue by indicating how to build hybrid accounting tables. While the proposal to integrate energy data is already in the Eurostat Guidelines (EC, 2009), it has never been applied in practice at sub-national level for road transportation. Our contribution is therefore original.

On the policy side, the problem of dealing with GHGs due to transportation is acute, and the application shows how important it is in this context to have robust estimates (i.e., to reduce uncertainty). Our case study highlights the value of tracking the indirect impact that all economic activities have on emissions due to traffic, i.e., as inputs to the transportation sector. This element is of consequence when the policy maker has to choose what kind of policy should be applied and which sectors to address.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2017.11.008.

References

Alam, Md.S., Duff, P., Hyde, B., McNabola, A., 2017. Improvement in the estimation and back-extrapolation of CO_2 emissions from the Irish road transport sector using a bottom-up data modelling approach. Transp. Res. Part D: Transp. Environ. 56, 18–32.
Bun, R., Jonas, M., Nahrsky, Z., 2015. Proceedings of 4th International Workshop on Uncertainty in Atmospheric Emissions. (IBSN 83-894-7557-X).
Dalmazzone, S., Notte, A., 2009. L'applicazione dell'approccio NAMEA per emissioni in atmosfera e rifiuti speciali a livello regionale, provinciale e comunale. Economia delle Fonti di Energia e dell'Ambiente 3. pp. 61–86.
Dalmazzone, S., La Notte, A., 2013. Multi-scale environmental accounting: methodological lessons from the application of NAMEA at sub-national levels. J. Environ. Manag. 130, 405–416.
European Commission, 2009. Manual for Air Emissions Accounts, KA-RA-09-004-EN.
European Commission, 2011. White paper on transport. In: Roadmap to a Single European Transport Area – Toward a Competitive and Resource-efficient Transport System. Luxembourg Publication Office of the European Union (ISBN 978-92-79-18270-9).
European Environmental Agency, 2014. Air Quality in Europe – 2014 Report. EEA Report No.5/2015. (ISSN 1977-8449, ISBN 978-92-9213-490-7).
European Environmental Agency, 2015. Air Quality in Europe – 2015 Report. EEA Report No.5/2015. (ISSN 1977-8449, ISBN 978-92-9213-701-4 702-1).
Eurostat, 2009. Manual for Air Emission Accounts, 2009 Edition. http://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/KS-RA-09-004 (accessed 06.06.2017).
Eurostat, 2015. Manual for Air Emissions Accounts, 2015 Edition. http://ec.europa.eu/eurostat/documents/3859598/7077248/KS-GQ-15-009-EN-N.pdf/ce75a7d2-4f3a-4f04-a4b1-747a6614eeb3 (accessed 06.06.2017).
Frey, H.C., Rubin, E.S., 1991. Development and Application of a Probabilistic Evaluation Method for Advanced Process Technologie. United States. http://dx.doi.org/10.2172/6253036. http://www.osti.gov/scitech/servlets/purl/6253036 (Accessed 06.06.2017).
Intergovernmental Panel on Climate Change, 2006. IPCC Guidelines for National Greenhouse Gas Inventories, Volume 1: General Guidance and Reporting. IPCC, Geneva, Switzerland.
Intergovernmental Panel on Climate Change, 1996. Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories. In: Volume 1: General Guidance and Reporting. IPCC, Geneva, Switzerland.
Intergovernmental Panel on Climate Change, 2014. Climate Change 2014: Fifth Assessment Report of the Intergovernmental Panel on Climate. IPCC, Geneva, Switzerland.
La Notte, A., Dalmazzone, S., 2012. Feasibility and uses of the NAMEA-type framework applied at local scale: case studies in North-Western Italy. In: Costantini, V., Mazzanti, M., Montini, A. (Eds.), Hybrid Economic-environmental Accounts, Routledge studies in Ecological Economics. Taylor & Francis Group, London and New York.
Linsmeier, T.J., Pearson, N.D., 2000. Value at risk. Financ. Anal. J. 56 (2), 47–67.
Marland, E., Cantrell, J., Kiser, K., Marland, G., Shirley, K., 2014. Valuing uncertainty part I: the impact of uncertainty in GHG accounting. Carbon Manag. 5 (1), 35–42.
McNeil, A., Frey, R., 2000. Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. J. Empir. Finance 7, 271–300.
Mensink, C., 2000. Validation of urban emission inventories. Environ. Monit. Assess. 65 (1–2), 31–39.
Morgan, J.P., 1996. RiskMetricsTM—Technical Document. Morgan Guaranty Trust Company of New York, pp. 296.
Nocera, S., Tonin, S., 2014. A joint probability density function for reducing the uncertainty of marginal social cost of carbon evaluation in transport planning. In: de Sousa, J.F., Rossi, R. (Eds.), Computer-based Modelling and Optimization in Transportation, Advances in Intelligent Systems and Computing. 262. pp. 126. http://dx.doi.org/10.1007/978-3-319-04630-3_9.
Nocera, S., Tonin, S., Cavallaro, F., 2015. The economic impact of greenhouse gas abatement through a meta-analysis: valuation, consequences and implications in terms of transport policy. Policy Transp. Policy 37, 31–43. http://dx.doi.org/10.1016/j.tranpol.2014.10.004.
Puliafito, S.E., Allende, D., Pinto, S., Castesana, P., 2015. High resolution inventory of GHG emissions of the road transport sector in Argentina. Atmos. Environ. 101, 303–311.
Rubin, L., Ranson, N., Shi, X., 2009. Analysis of Methods for Determining Margins for Uncertainty Under a Principle-based Framework for Life Insurance and Annuity Products. Price Waterhouse Coopers for the Society of Actuaries, London.
Singh, A., Gangopadhyay, S., Nanda, P.K., Bhattacharya, S., Sharma, C., Bhan, C., 2008. Trends of greenhouse gas emissions from the road transport sector in India. Sci. Total Environ. 390 (1), 124–131.
Tonin, S., La Notte, A., Nocera, S., 2016. A use-chain model to deal with uncertainties. A focus on GHG emission inventories. Carbon Manag. 7 (5–6), 347–359.
United Nation Framework Convention on Climatic Change, 2015. Draft Paris Agreement. Ad Hoc Working Group on the Durban Platform for Enhanced Action Second Session, Part Twelve. Paris, 29 November to 5 December 2015. available at. https://unfccc.int/files/bodies/awg/application/pdf/draft_paris_agreement_5dec15.pdf.
Valenzuela, M.M., Espinosa, M., Virgüez, E.A., Behrentz, E., 2017. Uncertainty of greenhouse gas emission models: a case in Colombia's transport sector. Trans. Res. Proc. 25, 4606–4622.
Weerahandi, S., 1993. Generalized confidence intervals. J. Am. Stat. Assoc. 88 (423), 899–905.
Zhao, Y., Nielsen, C.P., Lei, Y., McElroy, M.B., Hao, J., 2011. Quantifying the uncertainties of a bottom-up emission inventory of anthropogenic atmospheric pollutants in China. Atmos. Chem. Phys. 11, 2295–2308.

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